

Using Real-Time fMRI to Control a Dynamical System

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INTRODUCTION: Despite the enormous complexity of the human mind, fMRI techniques are able to partially observe the state of a brain in action. The brain state can be interpreted by a computer and the setup is then often called a *Brain Computer Interface* (BCI). We describe the development of a BCI. The BCI realizes a dynamical pole balancing experiment and is visualized in Figure 1. In the experiment, the subject was given the possibility to move a cart with an inverted pendulum on top of it. The cart could be pushed to the left or right by activating the parts of the motor cortex associated with movements of the left and right hand. Similar projects have been presented in [1] and [2]. However, the dynamical properties of the inverted pendulum make this a more challenging problem. We for example have to interpret the desire of the subject and set out a control signal moving the cart as often as once a second to have a chance to handle the fast dynamics of the pendulum.

METHODS: To distinguish between rest, left hand and right hand activation, a one layer neural network [3] was trained on a 240 second training data set. The training data set was generated by 20 seconds of left activity, followed by 20 seconds of right activity and then 20 seconds of rest. This sequence was repeated 4 times. A mask was used to train the neural network classifier on measurements from the brain only. Each volume was also filtered by a 3x3x3 Gaussian low pass filter.

In the real-time phase, each volume was spatially smoothed (3x3x3 Gaussian low pass filter) and detrended (using 45 old data volumes). A control signal (move the cart to the left, right or do nothing) was then computed by applying the, in the training phase computed, neural network. The control signal was used as an input to the dynamical pendulum system.

The data was acquired using a 1.5 T Philips Achieva MR scanner. The acquisition resolution was 80x80x10 voxels. Field of view and slice thickness were chosen to obtain a voxel size of 3x3x3 mm. Echo time (TE) was set to 40 ms and repetition time (TR) was set to 1000 ms. The classification was carried out in Matlab on a standard laptop.

RESULT: The subject was able to balance the inverse pendulum during a test run of 7 minutes (see <http://www.youtube.com/watch?v=HJL7j-uVqxA>). To further justify the success of the controller Figure 2 shows a validation run. The trained neural network was there applied, just as in the real-time phase, to a validation data set generated in the same way as the training data set. 93.7 % of the time samples were correctly classified and it took about 3-4 seconds for the system to detect a change of activity.

CONCLUSION: We have presented an fMRI based BCI realization. The human brain and a computer were here linked by fMRI and worked together as a controller of a dynamical system. The dynamical system was made up of a cart with an inverted pendulum mounted on top of it. The subject had the ability to induce a force by evoking brain activity in the motor cortex. A force was applied from the left if the subject activated the left hand and from the right if the subject activated the right hand. If the subject was resting no force was applied. A neural network was trained to separate between rest, activity induced by activating the left and right hand. The subject was able to balance the inverted pendulum during a 7 minute test run.

In the future we would like to improve the detection speed of the system. One way to do this is to train the classifier on the transitions between the different states instead of the states themselves, as mentioned in [1]. Another way is to look for the small undershoot of the BOLD signal. We would also like to increase the bandwidth of the bio feedback loop by including a larger number of different activities.

The developments here have a potential to aid people with communication disabilities e.g., locked in people.

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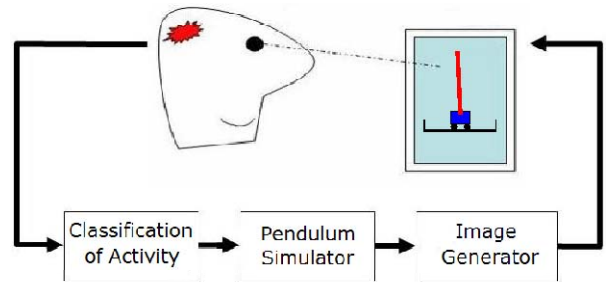


Fig 1. A schematic view of the BCI. The subject in the MR scanner sees the inverse pendulum mounted on a cart in a pair of VR-goggles. By resting, activating the left or right hand, the subject can push the cart and thereby balance the pendulum.

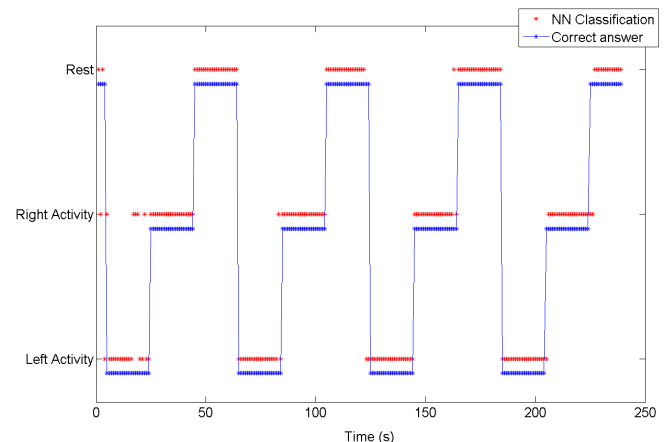


Fig. 2. The ability of the neural network to distinguish between rest, right hand activity and left hand activity in a validation data set. The blue dots show the physical action of the subject and the red dots the classified action of the neural network. The action was correctly classified at 224 out of 239 time points.